

IMPROVED DIGITAL WATERMARKING SCHEMES USING DCT AND NEURAL TECHNIQUES

A THESIS SUBMITTED IN PARTIAL FULFILLMENT
OF THE REQUIREMENTS FOR THE DEGREE OF

Bachelor of Technology
In
Computer Science and Engineering

By

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Department of Computer Science and Engineering
National Institute of Technology
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Department of Computer Science and Engineering

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**National Institute of Technology
Rourkela**

CERTIFICATE

This is to certify that the thesis entitled, “IMPROVED DIGITAL WATERMARKING SCHEMES USING DCT AND NEURAL NETWORKS” submitted by Hitesh Agarwal, Sapan Kumar Panda and Jayachandra Behera in partial fulfillment of the requirements for the award of Bachelor of Technology Degree in Computer Science and Engineering at the National Institute of Technology, Rourkela (Deemed University) is an authentic work carried out by them under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other university / institute for the award of any Degree or Diploma.

Date : 10 May ,2007

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ACKNOWLEDGEMENT

We express our sincere gratitude and indebtedness to **Dr. R.Baliarsingh**, Professor in the department of Computer Science and Engineering, NIT Rourkela for giving us the opportunity to work under him and extending every support possible at each stage of this project work. The level of flexibility offered by him in implementing the project work is highly applaudable.

We would also like to convey our deep regards to all other faculty members and staff of Department of Computer Science and Engineering, NIT Rourkela, who bestowed their great effort and guidance at appropriate times without which it would have been very difficult on our part to finish the project work.

Last but not the least we are indebted to our parents for inspiration and all of our friends who patiently extended all sorts of help for accomplishing this undertaking.

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ABSTRACT

The present thesis investigates the copyright protection by utilizing the digital watermarking of images. The basic spatial domain technique DCT based frequency based technique were studied and simulated. Most recently used Neural Network based DCT Scheme is also studied and simulated. The earlier used Back Propagation Network (BPN) is replaced by Radial Basis Function Neural Network (RBFNN) in the proposed scheme to improve the robustness and overall computation requirements. Since RBFNN requires less number of weights during training, the memory requirement is also less as compared to BPN.

Keywords : Digital Watermarking, Back Propagation Network (BPN), Hash Function, Radial Basis Function Neural Network (RBFNN), and Discrete Cosine Transform (DCT).

Watermarking can be considered as a special technique of steganography where one message is embedded in another and the two messages are related to each other in some way. The most common examples of watermarking are the presence of specific patterns in currency notes, which are visible only when the note is held to light, and logos in the background of printed text documents. The watermarking techniques prevent forgery and unauthorized replication of physical objects.

In digital watermarking a low-energy signal is imperceptibly embedded in another signal. The low-energy signal is called the watermark and it depicts some metadata, like security or rights information about the main signal. The main signal in which the watermark is embedded is referred to as the cover signal since it covers the watermark. In recent years the ease with which perfect copies can be made has lead large-scale unauthorized copying, which is a great concern to the music, film, book and software publishing industries. Because of this concern over copyright issues, a number of technologies are being developed to protect against illegal copying. One of these technologies is the use of digital watermarks. Watermarking embeds an ownership signal directly into the data. In this way, the signal is always present with the data.

Analysis

Digital watermarking techniques were implemented in the frequency domain using Discrete Cosine Transform (DCT). The DCT transforms a signal or image from the spatial domain to the frequency domain. Also digital watermarking was implemented using Neural Networks such as:

1. Back Propagation Network (BPN)
2. Radial Basis Function Neural Network (RBFNN)

Digital watermarking using RBFNN was proposed which improves both security and robustness of the image. It is based on the Cover's theorem which states that nonlinearly separable patterns can be separated linearly if the pattern is cast nonlinearly into a higher dimensional space. RBFNN contains an input layer, a hidden layer with nonlinear activation functions and an output layer with linear activation functions.

Results

The following results were obtained:-

1. The DCT based method is more robust than that of the LSB based method in the tested possible attacks. DCT method can achieve the following two goals: The first is that illegal users do not know the location of the embedded watermark in the image. The second is that a legal user can retrieve the embedded watermark from the altered image.
2. The RBFNN network is easier to train than the BPN network. The main advantage of the RBFNN over the BPN is the reduced computational cost in the training stage, while maintaining a good performance of approximation. Also less number of weights are required to be stored or less memory requirements for the verification and testing in a later stage.

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Chapter 1

GENERAL INTRODUCTION

- 1.1 Background
- 1.2 Motivation for Digital Watermarking
- 1.3 Layout of the Thesis

INTRODUCTION

1.1 Background

Watermarking is not a new technique. It is a descendent of a technique known as steganography, which has been in existence for at least a few hundred years. Steganography is a technique for concealed communication. In contrast to cryptography where the content of a communicated message is secret, in steganography the very existence of the message is a secret and only parties involved in the communication know its presence. Steganography is a technique where a secret message is hidden within another unrelated message and then communicated to the other party. Some of the techniques of steganography like use of invisible ink, word spacing patterns in a printed document, coding messages in music compositions, etc. have been used by military intelligence since the times of ancient Greek civilization.

Watermarking can be considered as a special technique of steganography where one message is embedded in another and the two messages are related to each other in some way. The most common examples of watermarking are the presence of specific patterns in currency notes, which are visible only when the note is held to light, and logos in the background of printed text documents. The watermarking techniques prevent forgery and unauthorized replication of physical objects.

Digital watermarking is similar to watermarking physical objects except that the watermarking technique is used for digital content instead of physical objects. In digital watermarking a low-energy signal is imperceptibly embedded in another signal. The low-energy signal is called the *watermark* and it depicts some metadata, like security or rights information about the main signal. The main signal in which the watermark is embedded is referred to as the *cover signal* since it covers the watermark. The cover signal is generally a still image, audio clip, video sequence or a text document in digital format.

The digital watermarking system essentially consists of a watermark embedder and a watermark detector (fig 1.1). The watermark embedder inserts a watermark into the cover signal and the watermark detector detects the presence of watermark signal. Note that the entity called the watermark key is used during the process of embedding and detecting watermarks. The watermark key has a one-to-one correspondence with the watermark signal (i.e. a unique watermark key exists for every watermark signal). The watermark key is private and known to

the authorized parties and it ensures that only the authorized parties can detect the watermark. Further, note that the communication channel can be noisy and hostile (i.e. is prone to attacks) and hence the digital watermarking techniques should be resilient to both noise as well as security attacks.

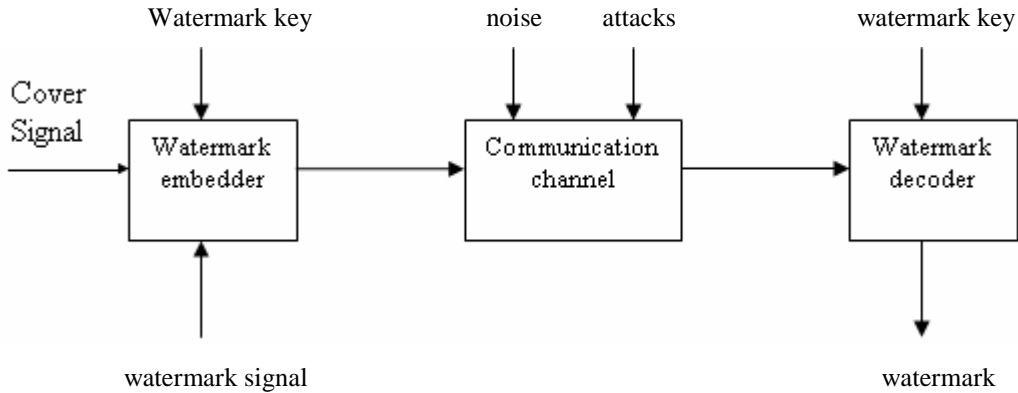


Fig 1.1: Digital Watermarking System

Definitions

Throughout this thesis, the notation and terminologies are used as per the definition specified at the first International Workshop of Information Hiding.

The information to be hidden (watermark, or in the general case of steganography, a secret message) embedded in a cover object (a cover CD, video or text), giving a stego object, which we may also call a marked object.

The embedding is performed with the help of a key, a secret variable that is in general known to the object's owner. Recovery of the embedded watermark may or may not require a key. If it does, the key may be equal to or derived from the key used in the embedding process.

1.2 Motivation for Digital Watermarking

In recent years it has been seen a rapid growth in network multimedia systems and other numerical technologies. This has led to an increasing awareness of how easy it is becoming to reproduce data. The ease with which perfect copies can be made may lead large-scale unauthorized copying, which is a great concern to the music, film, book and software publishing industries.

Because of this concern over copyright issues, a number of technologies are being developed to protect against illegal copying. One of these technologies is the use of digital watermarks. Watermarking embeds an ownership signal directly into the data. In this way, the signal is always present with the data.

Problems with Cryptography as a solution:

Many of the problems that we need to solve in enforcing copyright law for digital content are similar to problems in secure communications that have been solved using cryptography. For example, we may want to guarantee the integrity of the digital content when it is distributed, so that we can detect if it has been altered. Cryptography has also solved this problem called **non-repudiation**, in secure communications. Traditional cryptosystems suffer from one important drawback, however, which renders them useless for the purpose of enforcing copyright law: they do not permanently associate cryptographic information with content. Cryptographic techniques can hide a message from plain view during communication, and can also provide auxiliary information that effectively proves the message's integrity and guarantees non-repudiation; however cryptography does not embed information directly into the message itself. Thus cryptography alone can not make any guarantees about the **redistribution** or **alteration** of the content after it has initially passed through the cryptosystem. To provide the extended guarantees about the digital content, we need to extend the cryptographic techniques and embed additional information in the content itself. The techniques that have been proposed for solving this problem are collectively called **digital watermarking**.

1.3 Layout of the Thesis

The thesis report is organized as follows: Chapter 2 describes the Characteristics, Applications and Classifications of Digital watermarking. Chapter 3 deals with different watermarking techniques and also simulation results of the basic techniques like LSB modification and DCT based watermarking. Chapter 4 discusses the existing techniques of watermarking using MLPNN in DCT domain and the proposed RBFNN and DCT based algorithm and the results obtained thereof. Finally chapters 5 and 6 deal with conclusion of overall work and future enhancements.

Chapter 2

CHARACTERISTICS, APPLICATIONS AND CLASSIFICATIONS OF DIGITAL WATERMARKING

- 2.1 Characteristics of Digital Watermarking
- 2.2 Applications of Digital Watermarking
- 2.3 Classification of Digital Watermarking technique
- 2.4 Framework and parameters of Digital Watermarking

2.1 Characteristics of Digital Watermarking

Digital watermarking techniques have the following main features for embedding metadata in multimedia content

- **Imperceptibility:** The embedded watermarks are imperceptible both perceptually as well as statistically and do not alter the aesthetics of the multimedia content that is watermarked. The watermarks do not create visible artifacts in still images, alter the bit rate of the video or introduce audible frequencies in audio signals.
- **Robustness:** Depending on the application, the digital watermarking technique can support different levels of robustness against changes made to the watermarked image. If digital watermarking is used for ownership identification, then the watermark has to be robust against any modifications. The watermarks should not get degraded or destroyed as a result of unintentional or malicious signal and geometric distortions like analog-to digital conversions, digital-to-analog conversion, cropping, resampling, rotation, scaling and compression of the content. On the other hand, if it is used for content authentication, the watermarks should be fragile i.e. it should get destroyed whenever the content is modified so that any modification to content can be detected.
- **Inseparability:** After the digital content is embedded with watermark, separating the content from the watermark to retrieve the original content is not possible.
- **Security:** The digital watermarking techniques prevent unauthorized users from detecting and modifying the watermark embedded in the cover signal. Watermark keys ensure that only authorized users are able to detect/modify the watermark.

2.2 Applications of Digital Watermarking

Digital watermarking techniques have wide ranging applications. Some of the applications are enlisted below:

- **Copyright protection:** Digital watermarks can be used to identify and protect copyright ownership. Digital content can be embedded with watermarks depicting metadata identifying the copyright owners.
- **Copy protection:** Digital content can be watermarked to indicate that the content be illegally replicated. Devices capable of replication can then detect such watermarks and prevent unauthorized replication of the content.
- **Tracking:** Digital watermarks can be used to track the usage of digital content. Each copy of digital content can be uniquely watermarked with metadata specifying the authorized users of the content. Such watermarks can be used to detect illegal replication of content by identifying the users who replicated the content illegally. The watermarking techniques used for tracking is called **fingerprinting**.
- **Broadcast monitoring:** Digital watermarks can be used to monitor broadcasted content like television and broadcast radio signals. Advertising companies can use systems that can detect the broadcast of advertisements for billing purposes by identifying the watermarks broadcast along with the content.
- **Tamper proofing:** Digital watermarks, that are fragile, can be used for tamper proofing. Digital content can be embedded with fragile watermarks that get destroyed when any sort of modification is made to the content. Such watermarks can be used to authenticate the content.
- **Concealed communication:** Since watermarking is a special steganography it can be used for concealed communication also.

2.3 Classifications of Digital Watermarking Techniques

There are many watermark techniques in terms of their application areas and purposes. And they have different insertion and extraction techniques. In this section we have discussed some of the classification given by:

CLASSIFICATION		CONTENT
Inserted media category		Text, image, audio, video
Perceptivity of watermark		Visible, invisible
Robustness of watermark		Robust, semi-fragile, fragile
Inserting watermark type		Noise, Image format
Processing method	Spatial domain	LSB, Random function
	Transform domain	Look-up table, spread spectrum
Necessary data for extraction		Private, semi-private, public watermarking

Table 2.1: Classification of Watermarking according to several viewpoints

2.3.1 Classification according to inserted media

There have been many watermark researches for text and image so far, but video and audio watermark are also required along with wide-spread internet applications.

Text watermarking: It inserts a watermark in the font shape and the space between character and line spaces. This has some disadvantages as one cannot detect the watermark in case of modulating the font.

Image watermarking: This embeds special information and detects or extracts it later for ownership information. This approach is most widely

- *Video watermarking:* it is an extension of image watermarking. The method requires real time extraction and robustness for compression.
- *Audio watermarking:* this application area becomes a hot issue because of internet music, MP3. This approach needs watermark approaches and inaudibility like other cases.

2.3.2 Classification according to robustness, visibility and keys.

- *Robust and Fragile watermarking:* Robust watermarking is a technique in which modification to the watermarked content will not affect the watermark. As opposed to this, fragile watermarking is a technique in which watermark gets destroyed when watermarked content is modified or tampered with.
- *Visible and Transparent watermarking:* Visible watermarks are one which are embedded in visual content in such a way that they are visible when the content is viewed. Transparent watermarks are imperceptible.
- *Asymmetric & Symmetric watermarking:* Asymmetric watermarking (also called asymmetric key watermarking) is a technique where different keys are used for embedding and detecting the watermark. In symmetric watermarking (also called symmetric key watermarking) the same keys are used for embedding and detecting watermarks.

2.4 Frame work And Parameters

In order to identify important watermarking parameters and variables, we first need to have a look at the generic watermarking embedding and recovery schemes

Fig.2.1 illustrates the embedding process. Given an image I , a watermark W and a key K (usually the seed of a random number generator) the embedding process can be defined as a mapping of the form: $I*W*K \longrightarrow I'$ and is common to all watermarking methods.

The generic detecting process is depicted in Fig.2.2. Its output is either the recovered watermark W or some confidence measure indicating how likely it is for a given watermark at the input to be present in the image I' under inspection.

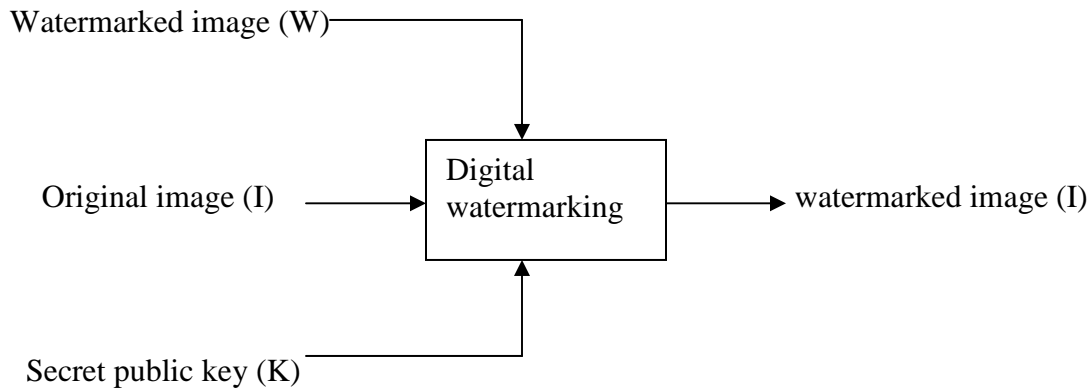


Fig 2.1: Embedding Watermark

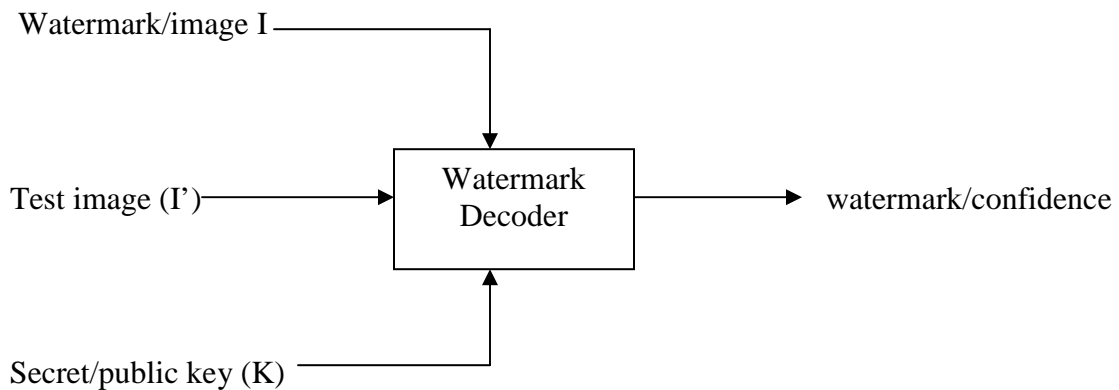


Fig 2.2: Detecting Watermark

There are several types of watermarking systems. They are classified by their inputs and outputs:

Private watermarking: systems require at least the original image. Type-1 systems extract the watermark W from the possibly distorted image I' and use the original image I as a hint to find where the watermark could be in I' i.e. $I'*I*K \longrightarrow W$. Type-2 systems also require a copy of the embedded watermark for extraction and just yield a 'yes' or a 'no' as to whether I' contains

W or not i.e. $I * I * K * W \longrightarrow \{0, 1\}$. This type of scheme is expected to be more robust since it conveys very little information.

Semi-private watermarking: does not use the original image for detection but answers the same question. The only use of private and semi-private watermarking seems to be evidence in court to prove ownership and copy-control in applications such as DVD where the reader needs to know whether it is allowed to play the content or not.

Public watermarking: remains the most challenging problem since it requires neither the secret original I, nor the watermark W. Indeed such systems really extract n bits of information from the watermarked image i.e. $I * K \longrightarrow W$. Public watermarks have much more applications than others and we have focused our work on these systems. Actually the embedding algorithms used in public systems can always be used into a private one to improve robustness at the same time.

After grouping different systems, we can now identify different parameters and variables.

Amount of embedded information: This is an important parameter since it directly influences the watermark robustness. The more information one wants to embed; the lower is the watermark robustness. The information to be hidden depends on the application.

Watermark embedding strength: There is a tradeoff between the watermark embedding strength and quality. Increased robustness requires stronger embedding, which in turn increases the visual degradation of the image.

Size and nature of the image: Although very small pictures have very low commercial value, watermarking technique needs to be able to recover a watermark from them. Photographers and stock companies have great concerns about having their work stolen and most of them still rely on small images, visible watermarks and even rollover java scripts to reduce infringement.

Secret information: although the amount of secret information has no direct impact on the visual fidelity of the image or the robustness of the watermark, it plays an important role in the security of the system. The key space i.e. the range of all possible values of the secret information should be large enough to make exhaustive search attacks impossible.

Chapter 3

DIGITAL WATERMARKING TECHNIQUES

CLASSIFICATION

- 3.1 Techniques in Spatial domain
- 3.2 Techniques in Frequency domain
- 3.3 Experimental results
- 3.4 Conclusion

The various watermarking techniques that have been suggested till date are classified into two categories. One is spatial domain and the other is frequency domain. The first method embeds a watermark into the cover signal in spatial domain. In general main advantage of this method is that it has a good computing performance, but the disadvantages are lower security and robustness. The second method embeds a watermark in the frequency domain of the cover signal. This method transforms the original data into the frequency domain. The watermark is then embedded after using a Fourier, discrete cosine or wavelet transform.

3.1 Techniques in spatial domain

3.1.1 Basic technique

The most straightforward way to embed a watermark is to add pseudorandom noise pattern to the intensity of the image pixels. The noise signal is usually integers like (-1, 0, 1) or sometimes floating point numbers. To ensure that the watermark can be detected, the noise is generated as a key, such that the correlation of the noise of different keys will be low. To create the watermarked image $I_w'(x, y)$ the pseudorandom pattern is multiplied by a small gain factor k , which is to control the energy of the watermark, and added to the host image $I(x, y)$ as shown by the following equation:

$$I_w'(x, y) = I(x, y) + k * W(x, y) \text{ ----- (1)}$$

In order to detect the watermark, the correlation between the images $I_w'(x, y)$ and the pseudorandom noise pattern $W(x, y)$ is computed. During the processing, the correlation will be much higher than the average when the key is the same as the pattern noise of the watermarked image. It is common to set a threshold T to decide whether the watermark is detected or not. The correlation is given as:

$$R_{I_w(x, y) W(x, y)} = \frac{1}{N} \sum_{i=1}^N I_{wi}(x, y) W_i(x, y) \text{ ----- (2)}$$

3.1.2 Least Significant Bit Modification

Least Significant bit (LSB) insertion is a common approach of embedding watermarks in the data. If each pixel in the gray level image is represented by an 8-bit value, the image can be

spliced up into 8-bit planes. Since the least significant bit plane does not contain visually significant information, it can easily be replaced by an enormous amount of watermark bits.

To hide the image in the LSBs of each byte of a 24-bit image, you can store 3 bits in each pixel. A 1024×768 bit image has the potential to hide a total of 2,359,296 bits of information. If you compress the watermark to be hidden before you embed it, you can hide a large amount of information. To the human eye, the resulting watermarked image will look identical, to the original image.

Example: The letter A can be hidden in 3 color pixels (assuming no compression). The original raster data of the 3 pixels (9 bytes) may be:

```
(00100111 11101001 11001000)
(00100111 11001000 11101001)
(11001000 00100111 11101001)
```

The binary value of A is 10000011. Inserting the binary value for A in 3 pixels would result in:

```
(00100111 11101000 11001000)
(00100110 11001000 11101000)
(11001001 00100111 11101001)
```

The underlined bits are the only four actually changed in the 8 bytes used. On average, LSB requires that only half the bits in an image be changed. You can hide data in the least and second least significant bits and still the human eye would not be able to discern it.

The LSB insertion methods for watermarks is not very secure and robust to processing techniques because the LSB plane can easily be replaced by random bits, effectively removing the watermark bits. It is also vulnerable to slight image manipulations. Converting an image from lossless compression to lossy compression and then back could also destroy the hidden information.

3.2 Techniques in Frequency Domain

3.2.1 Discrete cosine transform

The Discrete Cosine Transform (DCT) based watermarking scheme is a transform domain algorithm for embedding watermarks into images. Normally the DCT is used for

decomposing the host image into parts (or spectral sub-bands) of differing importance while taking the images visual quality into respect (Fig.3.1). The DCT transforms a signal or image from spatial domain to the frequency domain.

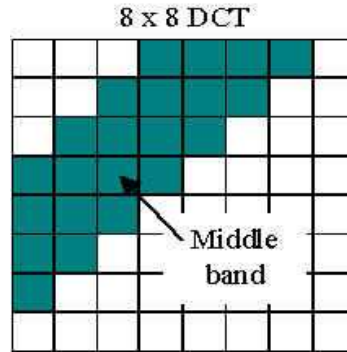


Fig 3.1:Defination of DCT Regions

The middle band is chosen as the embedding region as to provide additional resistance to lossy compression techniques, while avoiding significant modification of the cover image. A basic scheme of the watermark embedding and detecting in DCT is given in Fig.3.2.

3.2.2 DCT Watermark casting

Discrete Cosine Transform uses the cosine transform to represent original data. The watermark is cast by first computing the $N \times N$ DCT coefficient matrix of an $N \times N$ image. Where $A(i, j)$ is the intensity of the pixel in row i and column j . The DCT $T(u, v)$ is calculated as:

$$T(u, v) = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} A(i, j) \cdot \alpha(u) \alpha(v) \cdot \cos\left[\frac{(2i+1)u\pi}{2N}\right] \cos\left[\frac{(2j+1)v\pi}{2N}\right] \text{-----} (3)$$

Where $u, v = 0, 1, 2, 3, \dots, N-1$

$$\alpha(u) = \alpha(v) = \begin{cases} (1/N)^{0.5} & \text{for } u = 0 \\ (2/N)^{0.5} & \text{for } u = 1, 2, \dots, N-1 \end{cases}$$

The DCT coefficients are then reordered by the zigzag scan. For most images, much of the signal energy lies at low frequencies; these appear in the upper left corner of the DCT. The lower right values represent higher frequencies and are small enough to be neglected with little

visible distortion. The watermark is embedded by leaving the first L coefficients intact and only changing the last M coefficients where L+M is the total number of coefficients.

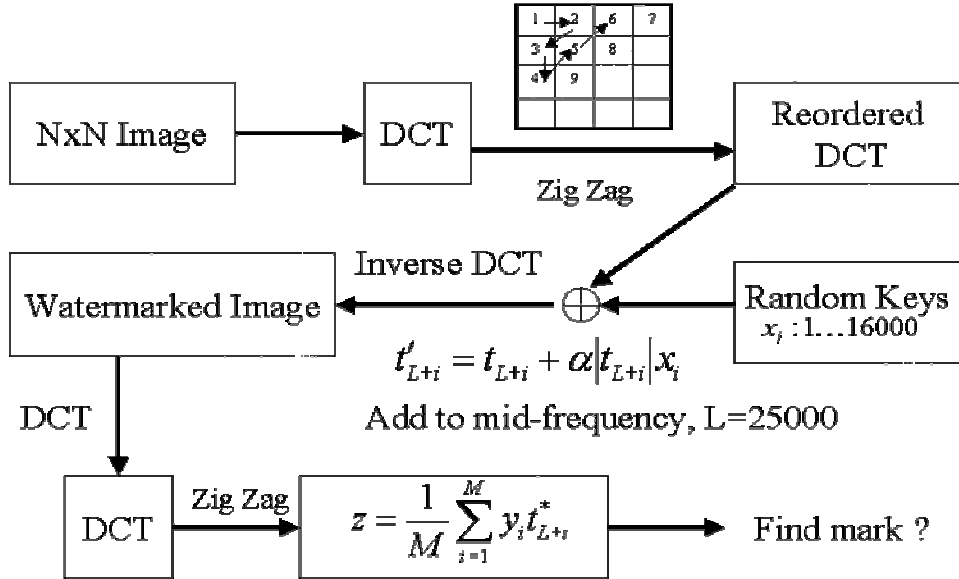


Fig 3.2. DCT Based Watermark

Assume the first L+M DCT coefficients are: $T = \{t_1, t_2, \dots, t_L, t_{L+1}, \dots, t_{L+M}\}$

$X = \{x_1, x_2, \dots, x_M\}$ is the pseudo-random watermark

$$t'_{L+i} = t_{L+i} + \alpha |t_{L+i}| x_i \quad \text{where } i = 1 \dots M$$

After modifying the DCT coefficient we take the inverse DCT to get the watermark image. The IDCT is defined as:

$$A(i, j) = \sum_{u=0}^{N-1} \sum_{v=0}^{N-1} T(u, v) \cdot \alpha(u) \alpha(v) \cdot \cos\left[\frac{(2i+1)u\pi}{2N}\right] \cos\left[\frac{(2j+1)v\pi}{2N}\right] \dots \dots \dots (4)$$

3.2.3 DCT Watermark Detection

In the detection process, given a corrupted image, the $N \times N$ DCT is computed, then re-ordered by the zigzag scan. The $L+1$ to $L+M$ coefficients are selected to form a vector T^* . The correlation of T^* and the mark Y is calculated as:

$$T^* = \{t_{L+1}^*, \dots, t_{L+M}^*\}$$

$$z = \frac{1}{M} Y \cdot T^* = \frac{1}{M} \sum_{i=1}^M y_i \cdot t_{L+i}^* \text{-----}(5)$$

By comparing the correlation z to a pre-defined threshold, it is possible to determine if the watermark exists or not.

Various studies have resulted in the prediction and minimization of the visual impact of the distortion caused by the watermark. Lossy compression can be anticipated by embedding the watermark in the same domain as the compression scheme used to process the image, thereby making the watermark more robust.

3.3 Experimental Results

Both the algorithms are simulated using MATLAB 6.5 in a Pentium-IV processor (2.4 GHz).

In image processing techniques, Peak Signal to Noise Ratio (PSNR) is usually used to assess the differences in the degree of image quality, from pre-processing to post-processing. A large value of PSNR means there is little difference between original image and processed image. A PSNR value greater than or equal to 30 means that the processed image quality is acceptable.

The efficacy index, Bit Code Ratio (BCR) is defined as:

$$BCR = \frac{\text{Number of pixels recovered as original}}{\text{size of watermark}} \text{-----} (6)$$

The watermarked image is subjected to low pass filtering, high pass filtering, cropping, Gaussian noise addition, salt and pepper noise addition and lossy compression. The retrieved watermarks from these distorted images are recognizable in some cases.

Fig 3.3 Result Images of DCT Based Method



Original Image (512 × 512)



JPEG Compressed



Original Watermark (39 × 39)



Retrieved Watermark



Watermarked Image



High Pass Filtered



Retrieved Watermark



Retrieved Watermark

3.4 Conclusion

The very earlier spatial domain LSB and the frequency domain technique DCT based Digital watermarking methods are simulated and the results are presented in tabular format. The DCT based method is more robust than that of the LSB based method in the tested possible attacks. This method can achieve the following two goals. The first is that illegal users do not know the location of the embedded watermark in the image. The second is that a legal user can retrieve the embedded watermark from the altered image.

Results show that the frequency domain techniques are more robust than the spatial domain techniques.

	BCR		PSNR(db)	
	LSB based method	DCT based method	LSB based method	DCT based method
Watermarked image	100	97.5	63.65	44.29
Attack				
Low pass filtering	0.59	88.29	29.92	29.89
High pass filtering	0.33	96.58	31.92	31.35
Cropping	83.23	90.07	17.99	17.14
Gaussian noise (0, 0, 1)	0.66	57.26	10.94	10.97
Salt and pepper noise (5%)	82.84	74.09	17.17	17.05
JPEG compression	0.72	95.53	37.58	36.89

Table 3.1: BCR % and PSNR (dB) of different test images in LSB and DCT methods

Chapter 4

DIGITAL WATERMARKING USING NEURAL NETWORKS

- 4.1 Watermarking using Back Propagation Network
- 4.2 Proposed method using RBFNN
- 4.3 Experimental Results
- 4.4 Discussion
- 4.5 Conclusion

A neural network is a potential tool in most of the signal processing and other application. Digital watermarking is not an exception where it finds a way to use neural network in order to make the process more secure and robust. Different models of neural network have their own merits and demerits. A BPN and DCT based watermarking is described below and subsequently a modified RBFNN is suggested to gain in terms of computational efficiency as well as memory requirements.

4.1 Watermarking using Back Propagation Network

In this section, brief discussion has been made on discrete cosine transform (DCT), the concept of one-way hash functions and the Back Propagation Network (BPN). The scheme is based on these foundations.

DCT can concentrate an image's energy into the left-upper corner. According to this characteristic, DCT has been used for image data compression, such as JPEG. Generally the DCT blocks (8×8) are not overlapped in its applications. In this scheme the DCT blocks are allowed to overlap partially. In this way, the security of the digital watermarking can be improved. In other words, a pirate can not exactly obtain the DCT block in this scheme.

The concept of one way hash function involves providing an arbitrary parameter x to a function h , which can easily produce an output value $z=h(x)$. However, it is difficult to produce x from the output value z . the characteristic of the one-way hash function is given x , it is difficult to find other x' such that $h(x')=h(x)$. To demonstrate the concept of one-way hash function, the following sample example is provided. Let $z=g^x \bmod p$, where g , x and p are 512 bits in length. It is simple to produce z using exponential operation but very difficult to produce x from z .

There are many famous one-way hash functions that have been applied, such as MD5 and SHA etc. In this scheme, a one-way hash function is used as given by Hwang to decide the location of the DCT blocks in which the watermark is to be hidden.

The Back Propagation Network (BPN) is one type of supervised learning neural network. It's a very popular model in neural networks. The principle behind BPN involves using the steepest gradient decent method to reach the smallest error tolerance.

The general model has architecture like depicted in Fig. 4.1. There are three types of layers, input layer, hidden layer and output layer. Each layer has one or more neurons or units. Each unit is fully connected to its adjacent layers or units. There may be more than one hidden layer, according to practical necessity. Two units of each adjacent layer are directly connected to each other called link. Each link has a weighted value, representing the relational degree between

the two units. Each input vector has its own mapping output vector in the BPN model. The computing functions of units are shown in Fig. 4.2. The details of the training algorithm are depicted below.

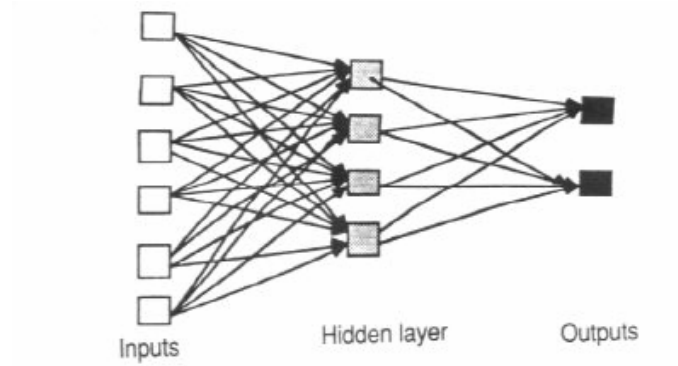


Fig 4.1 Architecture of a BPN network

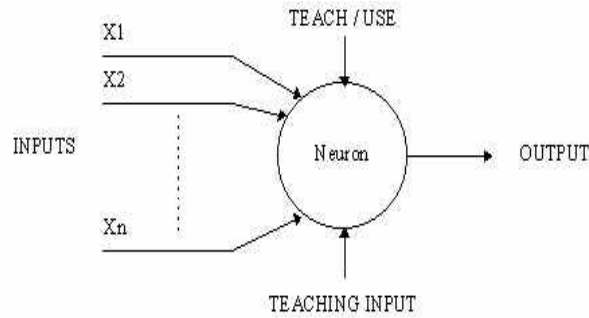


Fig 4.2 Layout of a single neuron

$$\text{net}_j(t) = \sum_i w_{ij} o_i(t) + \theta_j ,$$

$$\alpha_j(t+1) = f_{\text{act}}(\text{net}_j(t)) , \quad \text{-----}(7)$$

$$o_j(t) = f_{\text{out}}(\alpha_j(t)) ,$$

Where

j = index of some current unit.

i = index of a predecessor of the current unit j .

$\alpha_j(t)$ = activation of unit j in iteration t .

$f_{\text{act}}()$ = activation function.

$\text{net}_j(t)$ = input value in unit j in iteration t .

θ_j = threshold or bias of unit j.

w_{ij} =weight of the link from unit I to unit j.

$o_j(t)$ = output of unit j in iteration t.

$f_{out}()$ = output function.

The activation and output functions used in this scheme are defined as follows:

$$f_{act}(x) = 1/(1+e^{-x}) \quad \text{-----(8)}$$

0 if $x < 0$

$$f_{out}(x) = \begin{cases} 1 & \text{if } x > 0 \\ x & \text{otherwise} \end{cases} \quad \text{-----(9)}$$

The activation function $f_{act}(x)$, also called as sigmoid function, is the most popular function used in BPN. The differential of $f_{act}(x)$ is required in the training process to modify w_{ij} . The $f'_{act}(x)$ is equal to $f_{act}(x)(1 - f_{act}(x))$. In each iteration, we replace w_{ij} with $w_{ij} + \Delta w_{ij}$, called the generalized-delta rule, which is computed as shown below:

$$\Delta w_i = \eta * (D - Y) * o_i, \quad \text{-----(10)}$$

Where η is the learning factor, D is the desired output and Y is the actual output.

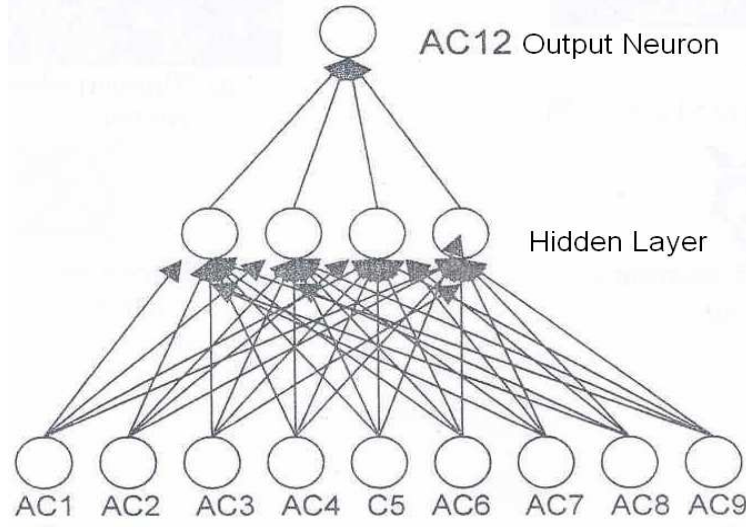


Fig 4.3 BPN Model used for Watermarking

Fig.4.3 is the BPN model given by Hwang . It has a hidden layer with four neurons. Generally, all initial weights $W1$ are assigned by random values. After training, we can use newer input vectors with w to predict the corresponding output vectors. We use this characteristic of BPN to learn the relationship between the DCT coefficients. The watermark is hidden by a changed DCT

coefficient, with one bit hidden in each DCT block. Since the relationship is recorded by whole weight and threshold values. We can retrieve the approximate original coefficients using these weights and thresholds. The watermark can be retrieved using changed coefficients and approximate original coefficient .

4.1.1 Watermark Embedding

1. After obtaining the DCT block for an image choose the first 9 coefficients (AC1-AC9) as the input vector and desired output as the AC12 for the i^{th} DCT block.
2. The inputs are expanded by the sigmoid function F_{act} .
3. Train the block using the BPN model until the MSE is minimum or constant.
4. Embed the binary watermark W_i by replacing the original AC12 $_i$ with AC12 $_i'$ where

$$\text{AC12}_i = \begin{cases} \text{AC12}_i - \delta & \text{if } W_i = 0 \\ \text{AC12}_i + \delta & \text{if } W_i = 1 \end{cases}$$

5. Repeat step 4 till all the bits of the watermark are embedded.
6. Take the inverse DCT to obtain the watermarked image.

4.1.2 Extracting the Watermark

1. Introduce the secret keys to obtain the DCT blocks.
2. Use the AC1,AC2.....AC9 coefficients of the i^{th} block as the inputs for the BPN architecture to get the observed AC12 $_i$ and then retrieve the watermark using

$$W'_i = \begin{cases} 0 & \text{if } \text{AC12}_i \leq \text{AC12}'_i \\ 1 & \text{if } \text{AC12}_i > \text{AC12}'_i \end{cases}$$

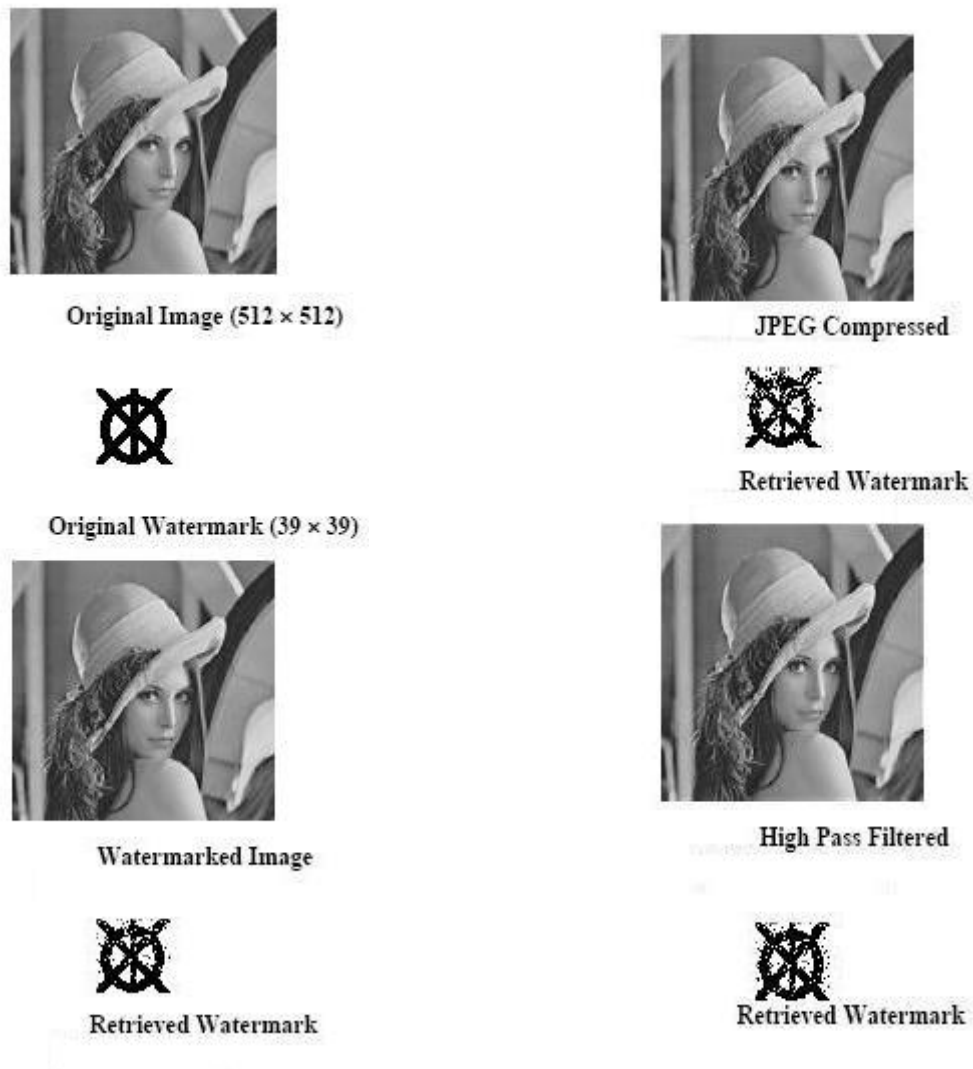
3. Compare the original watermark W and the extracted W'_i .

4.1.3 Simulation Results

Fig 4.4 shows the training process for the original lena image by using BPN model until the deserved goal is met. And the figures shown below are the simulated results of the watermarked

image on different type of attacks. The PSNR and the BCR values for these simulated results is shown in Table 3.

Fig 4.4 Result Images of BPN-DCT Based Method



4.2 Proposed Method using RBFNN

In this thesis; we have proposed a digital watermarking scheme, which embeds the watermark into the frequency domain. In this scheme, we have used a Radial Basis Function Neural Network (RBFNN) to improve both security and robustness of the watermarked image. A one-way hash function is also used in this scheme to decide the locations of the embedded watermark for enhancing security.

4.2.1 Radial Basis Function Neural Network (RBFNN)

The RBF network is a popular alternative to the MLP which, although it is not as well suited to larger applications, can offer advantages over the MLP in some applications. An RBF network can be easier to train than an MLP network. The main advantage of the RBFNN is the reduced computational cost in the training stage, while maintaining a good performance of approximation. Also less number of weights is required to store or less memory requirement for the verification or testing in a later stage.

Radial-Basis Function Networks used for pattern classification are based on Cover's theorem on the separability of patterns. This theorem states that nonlinearly separable patterns can be separated linearly if the pattern is cast nonlinearly into a higher dimensional space. Therefore we are looking for a network that converts the input to a higher dimension after which it can be classified using only one layer of neurons with linear activation functions.

That's why the structure of a RBFN is simple. It contains an input layer, a hidden layer with nonlinear activation functions and an output layer with linear activation functions. Fig-4.5 shows the architecture of a RBFNN.

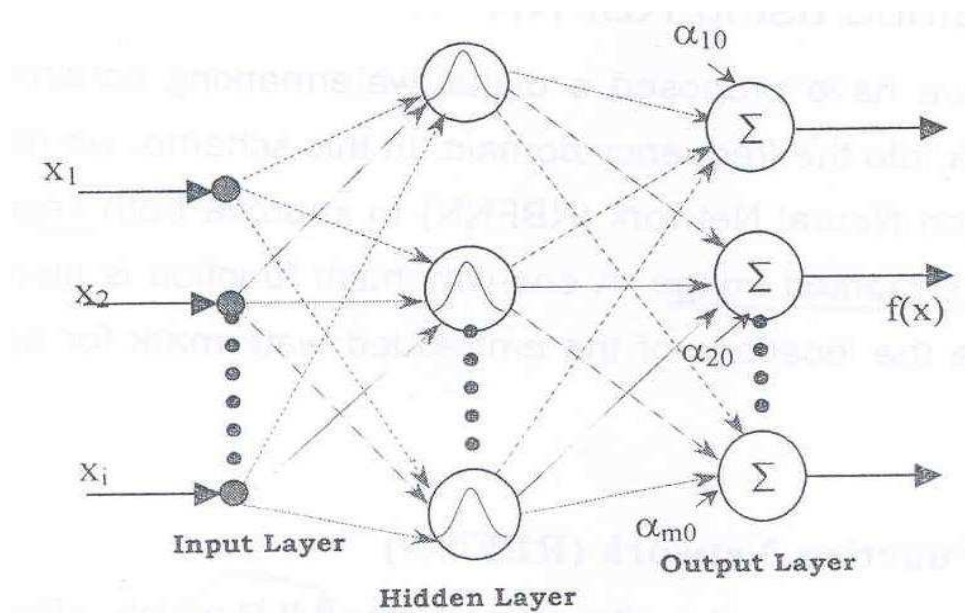


Fig 4.5 Radial Basis Neural Network Architecture

The RBF network has a similar form to the MLP in that it is a multi-layer, feed-forward network. However, unlike the MLP, the hidden units in the RBF are different from the units in the input and output layers: they contain the “Radial Basis Function”, a statistical transformation based on a Gaussian distribution from which the neural network’s name is derived. Like MLP neural networks, RBF networks are suited to applications such as pattern discrimination and classification, pattern recognition, interpolation, prediction and forecasting, and process modeling.

In the hidden layer of an RBF, each hidden unit takes as its input all the outputs of the input layer x_i . The hidden unit contains a “basis function” which has the parameters “center” and “width”. The center of the basis function is a vector of numbers c_1 of the same size as the inputs to the unit and there is normally a different center for each unit in the neural network. The first computation performed by the unit is to compute the “radial distance”, d , between the input vector x_i and the center of the basis function, typically using Euclidean distance:

$$d = \sqrt{((x_1 - c_1)^2 + (x_2 - c_2)^2 + \dots + (x_n - c_n)^2)}$$

The unit output a is then computed by applying the basis function B to this distance divided by the width σ :

$$v = B\left(\frac{d}{\sigma}\right)$$

The basis function is a curve (typically a Gaussian function), which has a peak at zero distance, and which falls to smaller values as the distance from the center increases. As a result, the unit gives an output of one when the input is “centered” but which reduces as the input becomes more distant from the center. There are three sets of variables that affect each nodes input to the solution, the position, the width and the output layer weight.

Several widely used basis functions are:

multiquadratics: $\phi(x) = \frac{1}{\sqrt{(x^2 + c^2)}}$ for some $c > 0$

inverse multiquadratics: $\phi(x) = 1/\sqrt{(x^2 + c^2)}$ for some $c > 0$

Gaussian: $\phi(x) = \exp(-x^2/2\sigma^2)$ for some $\sigma > 0$

Multivariate Gaussian: $\phi(x) = \exp(-\|x - c_i\|^2/2\sigma^2)$ for some $\sigma > 0$

The multivariate Gaussian function provides two important properties that make it a proper choice for building radial-basis functions: it is both translation and rotation *invariant*.

The output node is a linear node as described in the MLP with a linear summation of the weights and the outputs from the hidden Gaussian neurons

represented as
$$y_j = \sum_{i=1}^n w_{ji} \phi(x) + \theta_j \text{-----} (11)$$

Where w is the weight from the i^{th} hidden neuron to the output neuron and θ is the bias value to the j^{th} output neuron.

A flat network results for which only the connection weights and the bias term must be learned. Thus the back-propagation learning algorithm, used for adapting the RBFNN's parameters, becomes very simple

Back Propagation Training using LMS algorithm:

The optimization of the cost function of the RBFNN can be done by Gradient Descent technique by taking the partial derivative of the cost function with respect to each of the parameter of the RBFNN. The parameters of RBFNN include the centers, the variance of the hidden nodes and

the weights of the connecting path of the neural network. The training algorithm is derived as follows:

Let the error vector at the output unit is $e = (d - y)$, where d = desired output vector and y = estimated output vector. Let E denotes half of the square error vector and is considered as the cost function. Taking the partial derivative of E with respect to different network parameters the update equations for the center and width of the Gaussian function as well as the connecting and bias weights can be derived. The key equations obtained from the derivation are:

$$\Delta w_{ji} = n_1 e \phi_i(x, c) \text{-----} (12)$$

$$\Delta c_i = n_2 e w_i \frac{x - c_i}{\sigma^2} \phi(x, c) \text{ and } \Delta \sigma_i = n_3 e w_i \frac{(x - c_i)^2}{\sigma^3} \phi(x, c) \text{-----} (13)$$

Where n_1, n_2, n_3 are the learning parameters.

By applying each input pattern the change in the center location, width of the Gaussian function as well as the connecting and bias weights are computed. After all the patterns are applied, the average change of different parameters is calculated and different network parameters are updated once in each experiment. The update equation of the center position is given by

$$c_i(n+1) = c_i(n) + \frac{1}{T} \sum_{t=1}^T \Delta c_i(n) \text{-----} (14)$$

Similarly the update equations for other parameters at $(n+1)$ th iteration are given by

$$\sigma_k(n+1) = \sigma_k(n) + \frac{1}{T} \sum_{t=1}^T \Delta \sigma_k(n) \text{-----} (15)$$

$$w_{ji}(n+1) = w_{ji}(n) + \frac{1}{T} \sum_{t=1}^T \Delta w_{ji}(n) \text{-----} (16)$$

The main advantage of using RBFNN is that computational load is less compared to BPN and less number of weights are required at the time of testing the watermarked image.

In this scheme, RBFNN is used to learn the relationship between the DCT coefficients. The watermark is hidden by changing one of DCT coefficients. That is one bit of watermark is hidden in one DCT block. Since the relationship is trained before the coefficient is changed, that relationship is recorded using whole weights and threshold values. We can retrieve the

approximate original coefficients using these weights and thresholds. The watermark can be retrieved by the relationship between the changed coefficients and the approximate original coefficients.

4.2.2 Watermarking algorithm using RBFNN

Embedding of the Watermark

Step: I

Let O denotes an original image, which was used to embed a watermark that requires 8 bits per pixel. The original image is usually represented as two-dimensional (2D) arrays. We define O as follows:

$$O = \begin{matrix} O(1,1) & O(1,2) & \dots\dots\dots & O(1,O_w) \\ O(2,1) & O(2,2) & \dots\dots\dots & O(2,O_w) \\ \dots\dots\dots & \dots\dots\dots & O(i,j) & \dots\dots\dots \\ O(O_h,1) & O(O_h,2) & \dots\dots\dots & O(O_h,O_w) \end{matrix} \text{-----} (17)$$

Where $O(i, j)$ is an integer, $0 < O(i, j) < 255$, $1 < i < O_h$, $1 < j < O_w$ and are the original image's height and width, respectively.

A binary image watermark, W was used in this scheme. The watermark image must be meaningful proof for someone who owns the copyright of the original image. In general, a trademark of the enterprise can be selected as a watermark. A watermark is defined as follows.

$$W = \begin{matrix} W(1,1) & W(1,2) & \dots\dots\dots & W(1,O_w) \\ W(2,1) & W(2,2) & \dots\dots\dots & W(2,O_w) \\ \dots\dots\dots & \dots\dots\dots & W(i,j) & \dots\dots\dots \\ W(O_h,1) & W(O_h,2) & \dots\dots\dots & W(O_h,O_w) \end{matrix} \text{-----} (18)$$

Where $W(i, j)$ is a binary, $W(i,j) \in \{0,1\}$, $1 < i < W_h$, $1 < j < W_w$, W_h and W_w are the watermark's height and width respectively.

The watermark is represented as 2D arrays. In order to hide the watermark in the original image, we converted the stored 2D data into a one-dimensional array as follows.

$$W = (W_1 \dots W_k, \dots, W_h \times W_w),$$

Step: 2

Let two prime numbers, p and q are chosen, and let n be equal to the product of p and q. Two secret keys k_1 and k_2 are chosen by the images owner, which are used to decide the locations (x_1, y_1) where the watermark will be hidden. (x_i, y_i) is computed using the following location decision procedure.

1. Compute the initial location (X_i, Y_i) as follows.

$$X_1 = k_1^2 \bmod n, Y_1 = k_2^2 \bmod n, \\ x_1 = X_1 \bmod O_w, y_1 = Y_1 \bmod O_h.$$

2. Compute the other $(W_h \times W_w) - 1$ locations as follows

$$X_i = X_{i-1} \bmod n, Y_i = Y_{i-1} \bmod n, \\ x_i = X_i \bmod O_w, y_i = Y_i \bmod O_h, \text{-----(19)}$$

Where $i = 2, \dots, (W_h \times W_w)$. Using the same location must be avoided. In other words, If (x_i, y_i) have been chosen in this procedure, ignore the (x_i, y_i) location. After this step, we get $W_h \times W_w$, locations (x_i, y_i) These location are different from (x_1, y_1) and each other.

Therefore, using the location decision procedure, we can produce $W_h \times W_w$ available locations in total. Each location corresponds to a sub image M_i . Here M_i is produced using:

$$M_i = \text{Sub matrix } (0, x, x_{i+7}, y, y_{i+7}), 1 < i < W_h \times W_w,$$

Where the function sub matrix (.) denote acquiring a DCT block from the image 0's coordinate (x_i, y_i) to coordinate (x_{i+7}, y_{i+7}) . Maybe these blocks are partially overlapped (Fig.4.6). Next we make these M_i , to perform the DCT transformation.

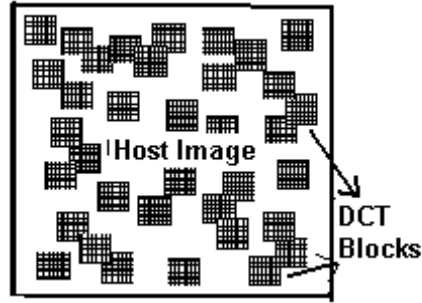


Fig 4.6 Selected overlapped DCT blocks

Step: 3

Choose the first nine AC coefficients ($AC1_i, AC2_i, \dots, AC9_i$) as the input vector and the twelfth AC coefficient $AC12_i$ is the output vector in the RBFNN model. The number of AC coefficients is shown in Fig 4.7. Note that $AC10, AC11, AC14$ are also candidates for the output vector. According to the DCT characteristic, as the AC number decreases, the robustness of the watermark increases at the same time the quantity of the watermarked image is decreased.

DC	1	5	6	14				
2	4	7	13					
3	8	12						
9	11							
10								

Fig 4.7: Number of AC Components

The RBFNN model used in our scheme is shown in fig 4.8. We take 9 AC coefficients as input.

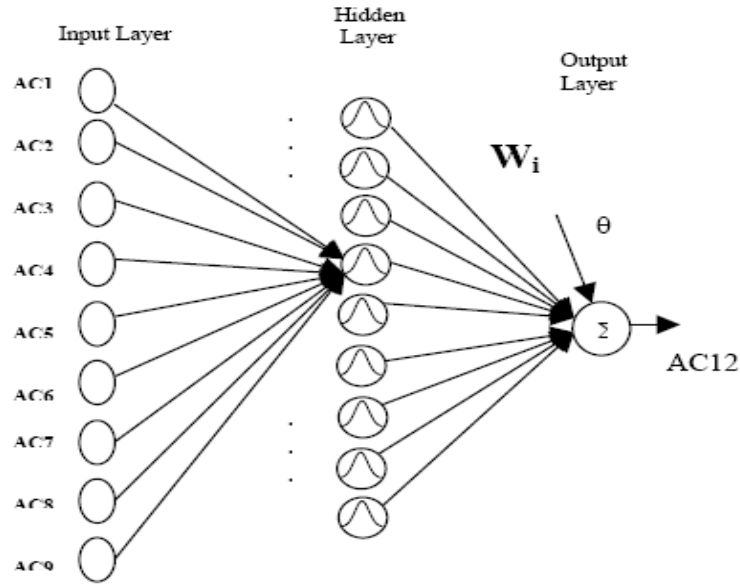


Figure IV RBFNN model used for watermarking

Fig 4.8

The initial weight w_{ij} and the threshold of RBFNN model are random values in this scheme. Weights are updated in the training; all weights w can be used as a secret key. The corresponding output vector $AC12_i'$ is acquired $AC12_i$ as:

$$AC12_i' = \text{net}_{AC12}$$

Here net_{AC12} is a function (i.e. $\tanh()$) defined in RBFNN model which outputs the value of node $AC12$

Step: 4

The watermark W_i is embedded by replacing the original $AC12_i$ with $AC12_i'$, where $AC12_i''$ is computed according to $AC12_i$ and W_i as follows.

$$AC12_i'' = AC12_i' - \sigma \text{ if } W_i = 0; \text{-----}(20) \\ AC12_i' + \sigma \text{ if } W_i = 1.$$

Here σ is a system parameter and is a constant, generally. A larger will result in a greater robustness in the watermarked image. But the distortion will be increased too. The value σ can be determined by the applicant's requirements.

Step: 5

After the twelfth coefficients are replaced and the inverse DCT is transformed, the embedding process is completed and we get the watermarked image.

Extracting of the Watermark

Step: 1

The retrieval procedure for the watermark from the watermarked image is similar to the embedding procedure. When the correct secret keys and weights are introduced, the corresponding $AC12_i$ and $AC12_i'$, can be obtained.

Step: 2

The retrieved watermark is produced using the relationship between $AC12_i$, and $AC12_i'$ as

$$\begin{aligned} W_i' &= 0 \text{ if } AC12_i < AC12_i'; \\ &1 \text{ if } AC12_i > AC12_i'. \end{aligned} \text{----- (21)}$$

Step: 3

The similarity between the original watermark W and the extracted watermark W is quantitatively measured by the bit correct ratio (BCR), defined as follows:

$$BCR = \frac{\sum_{i=1}^{w_h * w_w} w_i \otimes w_i'}{w_h * w_w} * 100\% \text{----- (22)}$$

Where w_i is the original watermark bit, w_i' is the extracted watermark bit, \otimes denotes the exclusive — OR operator.

4.3 Experimental Results

In image processing techniques, PSNR (Peak Signal to Noise Ratio) is usually used to assess the differences in the degree of image quality, from preprocessing to post-processing. A larger value of PSNR means there is a little difference between original image and processed image. A PSNR value greater than or equal to 30 means that the processed image quality is acceptable.

The algorithm is simulated using MATLAB 6.5 in a Pentium-IV processor (2.4GHz). Lena image is chosen as the cover signal where a logo is used as watermark signal. The BPN and RBFNN is trained using conventional back propagation algorithm and the saturated weights and biases are used for retrieving the watermark from the watermarked image. Fig. 4.9 depicts the MSE after 1000 epochs. In our experiment, we let σ is selected to be 20 and $n_1 = 0.2$, $n_2=0.15$ and $n_3=0.15$. We can see from Fig.15 that RBFNN has faster convergence characteristics than BPN and less Mean square Error.

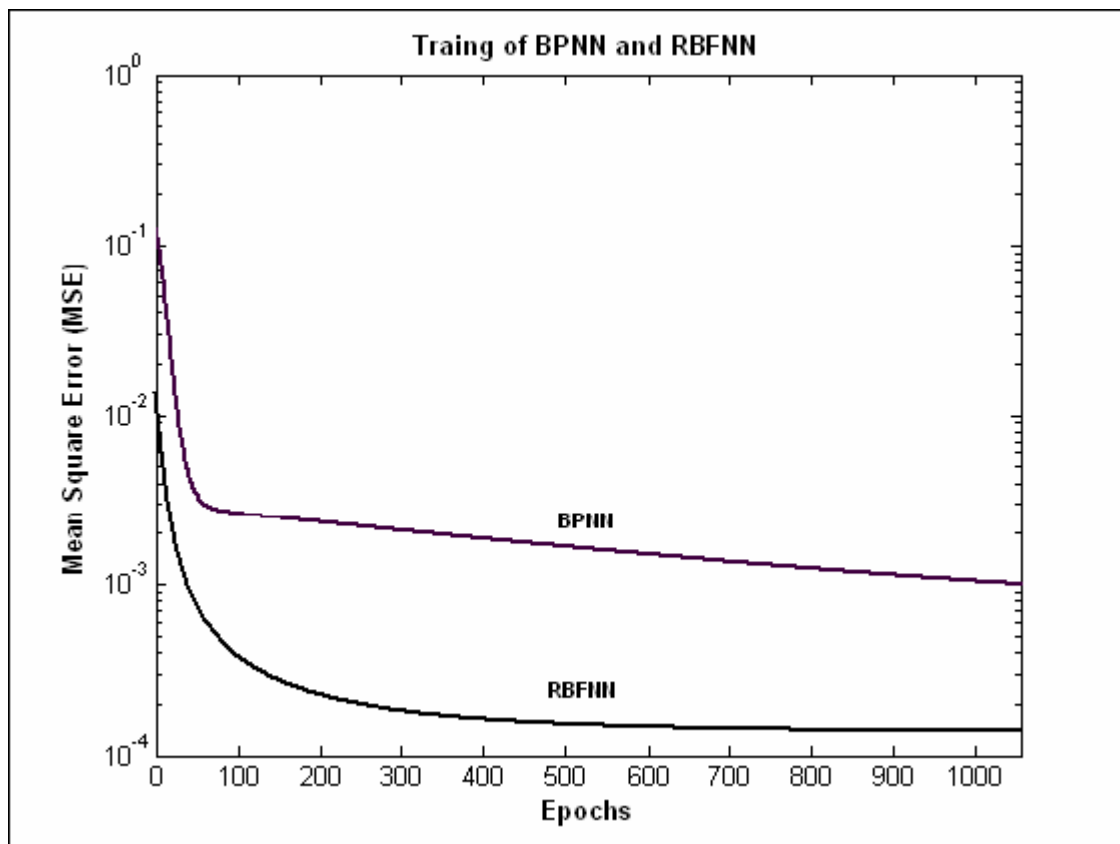


Fig 4.9 Variations of the MSE (Mean Square Error)

The original image of “Lena” (512 x 512, 8 bits / pixel) is shown in Fig. 4.10. The watermark is represented by (39 x 39) binary image. We used this scheme with the above parameter to embed watermark into original image to produce the watermarked image. The PSNR of the watermarked image is dB (using RBFNN). The retrieved watermark is shown in the figure. The efficacy index, Bit Correct Ratio (BCR) defined as:

$$\text{BCR} = \frac{\text{Number of pixels recovered as original}}{\text{size of watermark}} \text{-----} (23)$$

The BCR in our case (RBFNN) is found to be 93.1%, which conveys the superiority of the retrieval process over the BPN in which it is only 92.7%.

The watermarked image is subjected to low pass filtering, high pass filtering, Cropping, Gaussian noise addition, salt and pepper noise addition and lossy compression. The retrieved watermarks from these distorted images are recognizable in some cases. The retrieved watermarks from these distorted images are recognizable. The results are shown in the Fig.4.10

Three methods are compared and the results the given in Table 4.1. First method is DCT-based which is similar to BPN method, but does not use neural network. We have simulated the DCT-based watermarking using logo as watermark. In this we have chosen the DCT blocks by the hash function used in our algorithm. We just modify the ACI2 coefficient. From the table 4.1 we can see that its result is better than neural network method (BPN, RBFNN). But the disadvantage is that it requires the original image at the time of testing.

The main advantage of the RBFNN over BPN is the reduced computational cost in the training stage, while maintaining good performance of approximation. Also less number of weights is required to store or less memory requirement for the verification or testing in a later stage.

Fig 4.10 Result Images of RBFNN-DCT Based Method



Original Image (512 × 512)



JPEG Compressed



Original Watermark (39 × 39)



Retrieved Watermark



Watermarked Image



High Pass Filtered



Retrieved Watermark



Retrieved Watermark

BCR				PSNR (dB)			
DCT	BPN		RBFNN	DCT	BPN	RBFNN	
Watermarked Image	97.5		92.70	93.10	44.29	38.10	39.74
Low pass filtering	88.29		62.19	69.29	29.89	31.21	31.28
High pass filtering	96.58		90.29	91.39	31.35	30.58	30.99
Cropping	90.07		84.28	84.35	17.14	13.38	13.38
Gaussian noise addition	57.26		60.62	54.96	10.97	10.98	10.99
Salt & Pepper noise addition	74.09		70.28	69.36	17.05	18.07	18.05
JPEG compression	95.53		90.14	91.43	36.89	34.96	34.29

Table 4.1: BCR % and PSNR (dB) of different test images of Lena in BPN and RBFNN methods

4.4 Discussion

The secret keys used in the neural network-based watermarking scheme angled from 0 to n. The probability of directly destroying the Twelfth AC component of the watermarked image is very low. The probability is

$$\left(\frac{1}{O_h * O_w} \right)^{W_h * W_w} \text{-----(24)}$$

Where O_h and O_w are the image's height and width, and W_h and W_w are the watermark's height and width, respectively. Therefore the security of this scheme is very high.

The quality of the watermarked image is high (Fig.16(c)) in this scheme. In addition original image is not needed in the procedure of retrieving the watermark. Consequently this method has achieved the primary requirement for a reliable, high quality watermarking technique.

Because we allow partially overlapped DCT blocks, the retrieved watermark from a non-altered watermarked image has little noise. We can use non-overlapped DCT blocks to avoid this phenomenon. But it will reduce the security at the same time and be vulnerable to attack. The advantage of allowing partially overlapped DCT blocks is that there is no way to determine the exact position of the DCT blocks except by the owner of the property. The DCT coefficients on the left-upper corner suffered little change when the PSNR is larger than 30.

4.5 Conclusion

We have used Neural Networks and DCT for the digital watermarking of images. The RBFNN was used to improve the robustness of the proposed scheme. This method can achieve the following two goals. The first is that illegal users do not know the location of the embedded watermark in the image. The second is that a legal user can retrieve the embedded watermark from the altered (filtering, lossy compression, etc) image. We used RBFNN and DCT, in which blocks are allowed to partially overlap, to achieve this goal. The advantage of RBFNN over BPN is that we require less weights (i.e. half of BPN) to store or memory requirements is less, also less computation and has a good function approximation.

Chapter 5

CONCLUSION

5.1 Conclusion

In this thesis different existing digital watermarking methods are studied and attempts have been made to improve their performance in terms of robustness, security features and computational overhead. Exhaustive simulation has been done and results obtained thereof are compared to evaluate the performance of the proposed schemes.

5.2 Further Enhancements

In our proposed RBF model we are using the gradient decent training technique for updating the various parameters of the network. But this back propagation learning based on gradient decent technique is computationally expensive. Researchers have proved that training of RBF Networks using the Extended Kalman Filtering is quicker while providing the performance at the same level of index. Also new techniques can be applied to make the watermarking more robust.

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